Institut für Höhere Studien (IHS), Wien
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Institut für Höhere Studien
Stumpergasse 56, A -1060 Wien
Fax: +43/1/599 91-163

Adusei Jumah
Phone: +43/1/599 91-142
E-mail: jumah@ihs.ac.at

Robert M. Kunst
Phone: +43/1/599 91-255
E-mail: kunst@ihs.ac.at

Institut für Höhere Studien (IHS), Wien
Institute for Advanced Studies, Vienna

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Abstract

The paper investigates the extent to which the dollar/sterling exchange rate fluctuations affect coffee and cocoa futures prices on the London LIFFE and the New York CSCE by means of multivariate GARCH models – under the assumption that traders in perfectly competitive markets have equal access to all available information on changes in weather and in global demand and supply conditions. In three out of the four investigated cases, exchange rate posed as a main source of risk for the commodity futures price. The significance and form of volatility spill-over effects of a bilateral exchange rate are shown to be specific for commodity and market. A forecasting comparison on the basis of the identified models suggests that possible gains in prediction accuracy may be small.

Keywords
Commodity markets, multivariate GARCH models, exchange rates, volatility, forecasting

JEL Classifications
C32, C53, G15, Q14

Comments
We wish to thank Richard Baillie for providing us with a basic univariate GAUSS program code for the estimation of GARCH models that has helped us much in developing our bivariate ARCH model.

Contents

1 Introduction

Following the classic reference of the Dornbusch overshooting model (Dornbusch, 1976), modeling the link between exchange rates and commodity prices has received increased interest in the literature. Several subsequent studies have examined this link in various forms, relating exchange rates to border and/or internal prices of commodities. Very few studies have, however, examined the relationships between exchange rates and prices on commodity futures exchanges (e.g., Rausser and Walraven, 1988; Elfakhani and Wionzek, 1997) or between exchange rate volatility and relative price volatility of commodities (e.g., Bui and Pippenger 1987; Dupont and Juan-Ramon, 1996; Cuddington and Liang 1998). The lack of interest in the latter case might stem from the fact that asset return volatility is inherently unobservable.

Fuhrer (1993) argues that foreign exchange investors shift from one currency into another in large part because of the expected difference in returns to holding assets denominated in different currencies. If asset returns are expected to increase in one country relative to another, investors will shift into the former's currency and cause it to appreciate relative to the latter's currency. According to the interest rate parity condition, however, higher returns are linked to an expected exchange rate *depreciation*, if international financial markets are in equilibrium. Higher expected returns on a certain commodity in one country may still occur, assuming that risk-averse investors are reluctant to shift their asset holdings into that commodity. In this case, the commodity market will not substantially affect the exchange rate. Doukas and Arshanapalli (1991) have shown that a strong association exists between foreign exchange risk and relative price risk, which implies that corporations should simultaneously use forward currency and commodity futures instruments for optimal management of foreign exchange risk. Lately, Dupont and Juan-Ramon (1996) have examined the relations between fluctuations in real exchange rates among the major currencies and fluctuations in real commodity prices and suggest that increased exchange rate volatility calls for a better understanding of these relations.

The statistical properties of several commodity price series has been analyzed by Deaton and Laroque (1992) who detect non-normal skewness, leptokurtosis and serial correlation in returns. For this evidence of non-linear dynamic behavior and non-normality in distribution, they argue that the guarantee that the market as a whole can never carry negative inventories of storable commodities causes non-linear dynamic behavior in their prices. An alternative or complementary explanation could be that the volatility in the prices of storable commodities show dynamic clustering patterns that may be captured by GARCH (generalized autoregressive conditional heteroskedasticity, see BOLLERSLEV, 1986, and Section 3) models. The complexity of higher-dimensional models for volatility interaction might explain why existing research on commodity price volatility has centered on univariate models, even though many issues relevant to the analysis of volatility-based risk are essentially multivariate in nature.

The current study investigates the extent to which the dollar/sterling exchange-rate fluctuations affect the trade spread for cocoa and coffee between the London International Financial Futures and Options Exchange (LIFFE) and the New York Coffee, Sugar and Cocoa Exchange (CSCE) by means of multivariate GARCH models. In most situations, dramatic price movements in international agricultural commodity markets are associated *mainly* with adverse weather conditions in the major producing countries. However, traders in perfectly competitive markets have equal access to all available information on changes in weather and in global demand and supply conditions. Thus, an observed trade spread between markets may be explained by expectations on exchange rate fluctuations and hedging behavior of traders.

Analyses of price issues related to storable commodities are mostly based on 'basic fundamentals', i.e., on demand-supply models with competitive storage (see, e.g., DEATON AND LAROQUE, 1992). We rather follow the approach of CHAMBERS AND BAILEY (1996) by exploring the extent to which predictions can be obtained when statistical inferences, from practical necessity, must be made from prices alone, in the absence of data on quantities. Unlike the Dornbusch model, in which all goods prices except exchange rates are presumed to be sticky, we go along the lines of RAUSSER AND WALRAVEN (1988) by allowing agricultural commodity prices to be 'flexible'. In particular, we focus on futures prices, as they react much faster to new information than spot prices (see, e.g., JUMAH *et al.* 1999). Finally, we evaluate the model-based predictions on the basis of several cost functions and explore possible seasonal effects.

Cocoa and coffee together accounted for about nine percent of the value of developing countries' agricultural exports in 1996 (calculated from FAO, 1998). In particular, some countries in Sub-Saharan Africa depend substantially on the export of one or both commodities for their foreign exchange earnings. In the developed countries, cocoa and coffee are instrumental for the survival of certain giant multi-national corporations. Also, the LIFFE and CSCE are by far the two most important commodity exchanges for coffee and cocoa. Last, the dollar/sterling exchange rate still represents an important link in the international financial system despite the inception of the euro at the beginning of 1999.

While commodity price volatility remains a prime concern especially for developing countries, volatility in international currency markets presents an additional source of distress. At a time when developing countries are being urged to make use of derivative instruments as used on futures exchanges, as workable alternatives to their traditional price stabilization programs, the current paper examines the extent to which coffee and cocoa producing countries can hedge their export prices against the risk of major currency fluctuations, when using international futures exchanges.

The organization of the remainder of this paper is as follows. Section 2 describes the main features of coffee and cocoa markets and their exchange rate linkages. Section 3 summarizes the multivariate GARCH technique and presents the data. Section 4 reports and interprets the empirical results. Section 5 concludes.

2 Coffee and cocoa markets and their exchange rate linkages

Several studies have shown that the world market prices for coffee and cocoa are very volatile (UNCTAD, 1989; Deaton and Laroque, 1992; Deaton and Miller, 1995). The volatility in prices is *usually* attributed to supply factors, such as: weather conditions and occasional incidences of diseases and pests; switches between farm enterprises coupled with dynamic changes in farm production technology; commonplace disruption of the supply chain which emanates from inadequate infrastructural facilities, wars, etc. Other important sources of volatility are domestic policies in the major producing countries. Recently, however, findings by Cuddington and Liang (1998) indicate that exchange rate arrangements may imply an important source of systematic risk to world commodity trade. Large exchange-rate fluctuations of the floating-rate period have been found to be associated with much higher real commodity price volatility than during the fixed-rate periods. Earlier on, Deaton and Miller (1995) had observed that, in an age of fluctuating exchange rates, the mechanical effect of denominating the price of a commodity in a single currency can increase the volatility of the commodity price.

Traditional national strategies for dampening these price fluctuations are costly in budgetary terms and they also impair the efficiency of resource allocation and overall social welfare (see, e.g., Tyers and Anderson, 1992). Parikh *et al.* (1988) observed that, in general, international negotiations concerning agricultural trade focus on instability and distortions in international markets but, ironically, domestic policies which cause the distortions are outside the scope of these negotiations.

With market liberalization, the private sector is taking steps to develop new price risk management instruments such as derivatives on futures exchanges. Morgan *et al.* (1994) suggest that associated futures markets for coffee and cocoa exhibit efficiency in terms of price discovery and risk reduction and therefore provide, in theory, a viable policy alternative for developing economies. Considerable amounts of global supply of coffee and cocoa are traded on the CSCE and the LIFFE which are by far the largest exchanges for these two commodities. There are two main coffee species: arabica coffee, cultivated mostly in Latin America, has a milder taste and generally commands a price premium over robusta, which is grown mostly in Africa and South East Asia, has a stronger taste and is mainly used in blends and instant coffee. Atkin (1989) stresses that the distinction between arabica and robusta is crucial for futures markets, because London trades robusta whilst New York trades arabica. Trading in cocoa follows a similar pattern to that of coffee. The New York futures contract tends to reflect availability of Brazilian cocoa, although all cocoa is deliverable. Similarly, the London market reflects West African cocoa. However, as compared to the coffee market, the differences between the New York and London contracts for cocoa are of much smaller significance to the futures traders.

In financial markets, the traditional approach to currency management for investors with international portfolios has been either to ignore the foreign exchange risk, assuming that the benefits from asset diversification in international markets cannot be enhanced by hedging the exchange risk (see, e.g., Akdogan, 1996), or to hedge all assets completely. Although it may be true that currencies eventually return to equilibrium, implying that the returns from hedging foreign exchange rate exposures are zero in the long run, the first option has been disproved (at least in the short to medium term) by the impacts on asset prices of the recent currency crises in emerging markets, the dollar's violent fall against the yen in the autumn of 1998, and the euro's fall since the beginning of 1999. The second option can also be very costly: hedging certain currency risk exposures often means that the cost of hedging outweighs the gain in yield.

Based on these insights, we provide empirical evidence on the dynamic effects of the dollar/sterling exchange rate volatility on the prices of coffee and cocoa traded on the CSCE and the LIFFE and then recommend optimal hedging strategies against dollar/sterling exposures on these exchanges — relying on model-based predictions of several cost functions. The policy implication here is that improved volatility forecasts should result in more accurate asset prices.

3 Methodology

3.1 Bivariate ARCH models

The investigation of autoregressive conditional heteroskedasticity (ARCH) was motivated by the empirical observation of temporal clustering of volatility in financial time series that otherwise follow the theory-based martingale property for prices on efficient markets. The original ARCH model by Engle (1982) makes a Gaussian assumption for the underlying distribution and specifies a lag polynomial for second-order dependence:

$$\varepsilon_t = \nu_t \sqrt{h_t} \quad , \quad h_t = c + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 \quad , \quad \nu_t \sim \text{i.i.d. } N(0,1).$$

The GARCH model ('general ARCH') of Bollerslev (1986) generalizes the lag polynomial form to a rational function. The most common GARCH model is the GARCH(1,1) model and multivariate extensions are almost exclusively restricted to this specification, as the proliferation of parameters is a great problem for multivariate models. In the following, we use a notation similar to Gourieroux (1997). From this work, we also adopt the view that ARCH models are descriptions of the conditional-moments structure of the variables ('weak ARCH') and hence we will not explicitly specify distributional assumptions. This also implies that estimation by Gaussian maximum-likelihood (ML) methods is to be seen as 'quasi–ML'.

For scalar martingale-difference ε_t, the GARCH(1,1) model reads

$$\begin{aligned}\mathsf{E}(\varepsilon_t|\mathcal{F}_{t-1}) &= 0 \quad , \\ \mathsf{E}(\varepsilon_t^2|\mathcal{F}_{t-1}) &= h_t = c + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad .\end{aligned}$$

The filtration $\mathcal{F}_t$ is built from information sets that typically are generated by the past of the process ε_t and hence include the past of h_t if the model is stable. Coefficients are subject to the *admissibility* restrictions $c > 0, \alpha \geq 0, \beta \geq 0, (\alpha, \beta) \notin \{0\} \times (0, \infty)$. The first and last conditions avoid eventual degeneration, and the non-negativity constraints avoid negative h_t. The *stability* conditions are more involved (see NELSON, 1990), and most researchers focus on the case where $\alpha + \beta \leq 1, \beta < 1$, which guarantees the existence of the unconditional second moment $\mathsf{E}(\varepsilon_t^2)$ if $\alpha+\beta < 1$ and includes the interesting borderline 'IGARCH' case with $\mathsf{E}(|\varepsilon_t|^\delta) < \infty$ for $\delta \in (0, 2)$ if $\alpha + \beta = 1$.

In principle, an extension of the GARCH(1,1) model to higher dimensions is straightforward, as all scalar coefficients are simply replaced by matrix coefficients

$$\begin{aligned}\mathsf{E}(\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1}) &= \mathbf{0} \quad , \\ \mathsf{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'|\mathcal{F}_{t-1}) &= \mathbf{H}_t \\ \operatorname{vech}(\mathbf{H}_t) &= \operatorname{vech}(\mathbf{C}) + \tilde{\mathbf{A}} \operatorname{vech}(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}') + \tilde{\mathbf{B}} \operatorname{vech}(\mathbf{H}_{t-1}) \quad ,\end{aligned} \tag{1}$$

where we use the notation $\boldsymbol{\varepsilon}_t = (\varepsilon_{t1}, \ldots, \varepsilon_{tn})'$ for the vector of white-noise observations. Again, system *stability* depends on the properties of the $\{n(n+1)/2\} \times \{n(n+1)/2\}$–matrices $\tilde{\mathbf{A}}$ and $\tilde{\mathbf{B}}$, though such conditions are now becoming increasingly complicated.

In practice, the application of such multivariate GARCH models faces two main problems. First, the joint estimation of the matrix coefficients quickly exhausts the degrees of freedom, particularly if the system dimension n becomes large. Second, the imposition of the *admissibility* conditions during estimation is extremely difficult. One possible way out would be to formulate the model as

$$\mathbf{H}_t = \mathbf{C}^* + (\mathbf{I} \otimes \boldsymbol{\varepsilon}_{t-1}')\mathbf{A}^*(\mathbf{I} \otimes \boldsymbol{\varepsilon}_{t-1}) + \mathsf{E}\{(\mathbf{I} \otimes \boldsymbol{\varepsilon}_{t-1}')\mathbf{B}^*(\mathbf{I} \otimes \boldsymbol{\varepsilon}_{t-1}')|\mathcal{F}_{t-1}\} \tag{2}$$

and to restrict attention to semi-definite matrices $\mathbf{A}^*$ and $\mathbf{B}^*$. The specification (2) still faces the problem of an excessive dimension of the parameter space. It is also difficult to match the parameters in (2) to those in the regression formulation (1) which may be more convenient for prediction and analysis. The solution that is commonly used in the literature is to restrict the general model by imposing additional technical or theory-based assumptions. For example, BABA *et al.* (1991) use the leading terms in a spectral expansion only, whereas BOLLERSLEV (1990) assumes constancy of conditional correlations. Also, block-diagonality may be imposed on $\mathbf{A}^*$. A block-diagonal $\mathbf{A}^*$ means constant conditional covariances whereas conditional variances are allowed to depend on linear combinations of the $\boldsymbol{\varepsilon}$ coordinates. This closes the model class under rotations of the conditioning variables.

A different kind of simplification is considered, for example, by HOLT AND ARADHYULA (1990) who model the ARCH part univariately in an otherwise multivariate model. Although this approach is founded in theory in certain applications, we prefer to start with a multivariate ARCH model and to test whether such strong restrictions really hold.

Alternatively, we will focus on the case $\mathbf{B}^* = \mathbf{0}$, i.e., the ARCH(1) model. The restriction $\mathbf{B}^* = \mathbf{0}$ is motivated by the fact that, in tentative estimation for our data sets (unreported), the two GARCH parameters α and β turned out to be poorly identified even in the univariate models. Joint estimation of $\mathbf{A}^*$ and $\mathbf{B}^*$ in the bivariate model may cause even more numerical difficulties and impede convergence altogether.

We adopt a variant of the block-diagonal design that allows for a certain reaction of conditional covariances. Moreover, we will include a first-order MA term in the specification for the conditional expectation. In detail, we use the MA-ARCH specification

$$\begin{aligned}
\mathbf{X}_t &= \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t + \boldsymbol{\Theta}\boldsymbol{\varepsilon}_{t-1} \quad , \\
\mathsf{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') &= \mathbf{H}_t \quad , \\
\mathbf{H}_t &= \mathbf{L}_c\mathbf{D}_c\mathbf{L}_c' + \mathbf{L}\,\mathrm{diag}(\boldsymbol{\varepsilon}_{t-1}'\mathbf{A}\boldsymbol{\varepsilon}_{t-1}, \boldsymbol{\varepsilon}_{t-1}'\mathbf{B}\boldsymbol{\varepsilon}_{t-1})\mathbf{L}' \quad .
\end{aligned} \tag{3}$$

The matrices $\mathbf{L}$ and $\mathbf{L}_c$ are triangular matrices with unit diagonals, whereas $\mathbf{D}_c$ is a diagonal matrix with positive entries. For bivariate systems, the model has 16 parameters: 2 intercepts in $\boldsymbol{\mu}$, 4 entries in the 2×2–matrix $\boldsymbol{\Theta}$, 2 rotation parameters in $\mathbf{L}$ and $\mathbf{L}_c$, 2 elements in $\mathbf{D}_c$, and each 3 elements in the positive definite matrices $\mathbf{A}$ and $\mathbf{B}$. For computational convenience, these two matrices have also been re-parameterized in a Cholesky form. This model has appeared for the first time in KUNST AND SAEZ (1994).

We note that the system model has its 'normal' form when $\mathbf{L} = \mathbf{L}_c = \mathbf{I}$.

Then, covariances are 0 and the ARCH effects decompose into two independent variates. Another interesting case occurs if e.g. $\mathbf{B} = \mathbf{0}$ and the variation of volatility in both variates is explained by a single factor. The latter case and similar events of degeneration deserve special attention, as they cause non-identifiability of some parameters and, in practice, numerical problems. A third case of special interest is $\mathbf{A} = \text{diag}(a_{11}, 0), \mathbf{B} = \text{diag}(0, b_{22})$. Then, conditional heteroskedasticity is fully described by squared past errors. Otherwise, more general quadratic forms are needed. A slight generalization of this special case occurs if $\mathbf{A}$ or $\mathbf{B}$ are singular. If $\mathbf{A}$ has rank one, it can be represented as $(a_1, a_2)' (a_1, a_2)$ and conditional variance in the first error is explained by a single lagged 'factor' $(a_1\varepsilon_{t-1,1} + a_2\varepsilon_{t-1,2})^2$.

If both $\mathbf{A}$ and $\mathbf{B}$ have full rank, volatility in the system is described by four different combinations of past errors. It follows that the model can be poorly identified for many parameter values. Therefore, it pays to use the fully parameterized model in a first tentative experiment and then to impose restrictions as inspired by the insignificance of certain parameters.

3.2 Data characteristics

We examine the logarithmic monthly futures prices for coffee and cocoa on the LIFFE and the CSCE. Time ranges of available data were 1975:1–1995:6 for cocoa prices, and 1981:1–1995:12 for coffee prices. Logarithmic data on commodity prices are well known to be described accurately by difference-stationary models. See, for example, the related work by Karbuz and Jumah (1995) and Jumah *et al.* (1999), which considers similar data over slightly different periods, and the contribution by Reinhart and Wickham (1994) who stress important implications of difference stationarity for stabilization policy issues. Hence, we focus on first differences of the original data series.

In contrast to the behavior of speculative prices in efficient markets, however, commodity prices typically do not follow pure random walks. In order to explain this empirical observation, Deaton and Laroque (1992) argue that the random-walk model would imply the unit persistence of all shocks, which is unlikely in the presence of largely weather-determined price fluctuations.

Additionally, we include the dollar/sterling exchange rate in our investigation. The 1975–1995 time range, which was implied by the availability of the futures price data, corresponds with the floating exchange regime and thus allows us to effectively capture the dynamic effects of the dollar/sterling exchange volatility on the respective commodity prices.

Data for coffee and cocoa are from the International Coffee Organization and the International Cocoa Organization, respectively.

Figures 1–3 give a graphical summary of the data. To make the prices in New York and London comparable, all commodity futures prices were transformed into sterling and into metric tons before taking logarithms. Such standardization was avoided, however, in the statistical analysis, as it would have blurred the distinction of volatility components that are specific either to the exchange rate or to commodity futures prices. Figure 2 reveals that most of the time the cocoa prices were slightly higher on the LIFFE, while Figure 3 shows that the coffee prices reflect the persistent quality difference between robusta and arabica.

Table 1 gives the results from fitting simple univariate first-order moving-average models with first-order ARCH effects in the errors to the individual series. Both coffee futures prices show significant conditional heteroskedasticity. In contrast, ARCH effects in the cocoa prices are weak. Note that the price changes show significant positive autocorrelation. We also used higher-order ARMA models and higher-order ARCH and GARCH specifications, without any change in the qualitative features. Finally, we note that, although leptokurtosis and time-dependent volatility are also present in the exchange-rate series (unreported), ARCH effects are considerably stronger in the coffee prices.

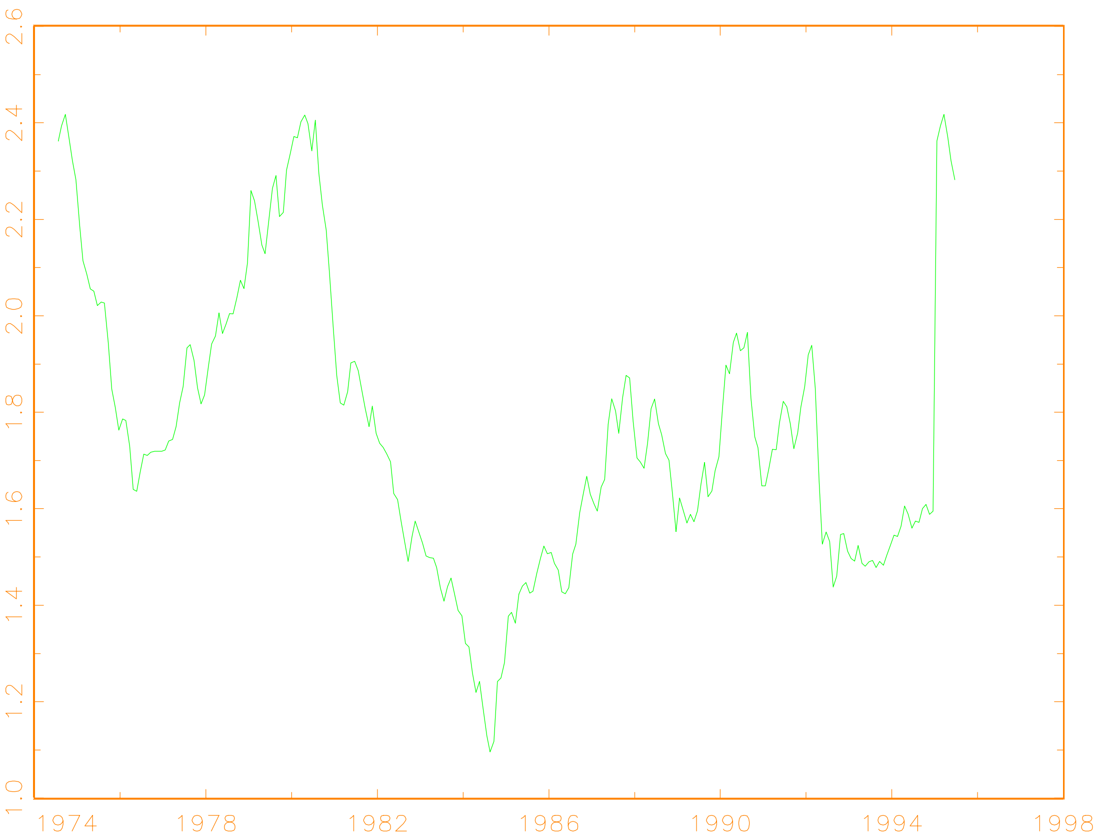

Figure 1: Dollar/sterling exchange rate 1975–1995.

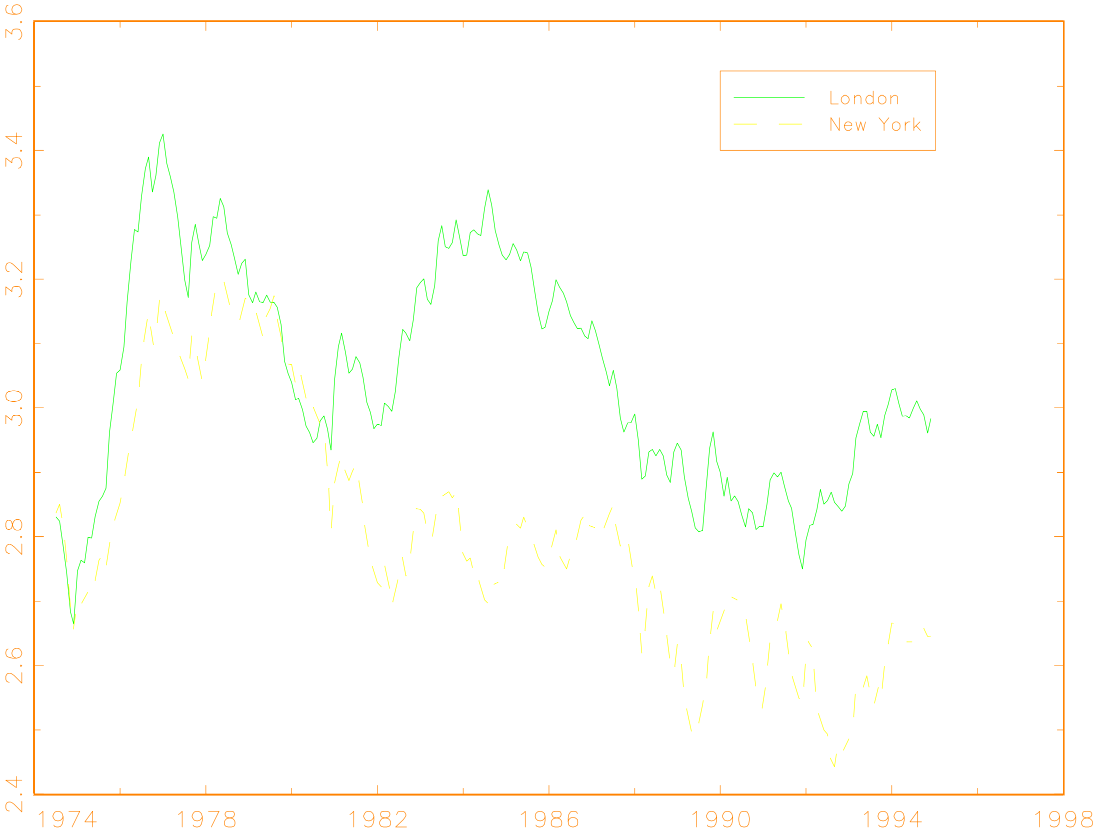

Figure 2: Logarithmic prices of cocoa futures on the LIFFE and CSCE for the period 1975:1–1995:10.

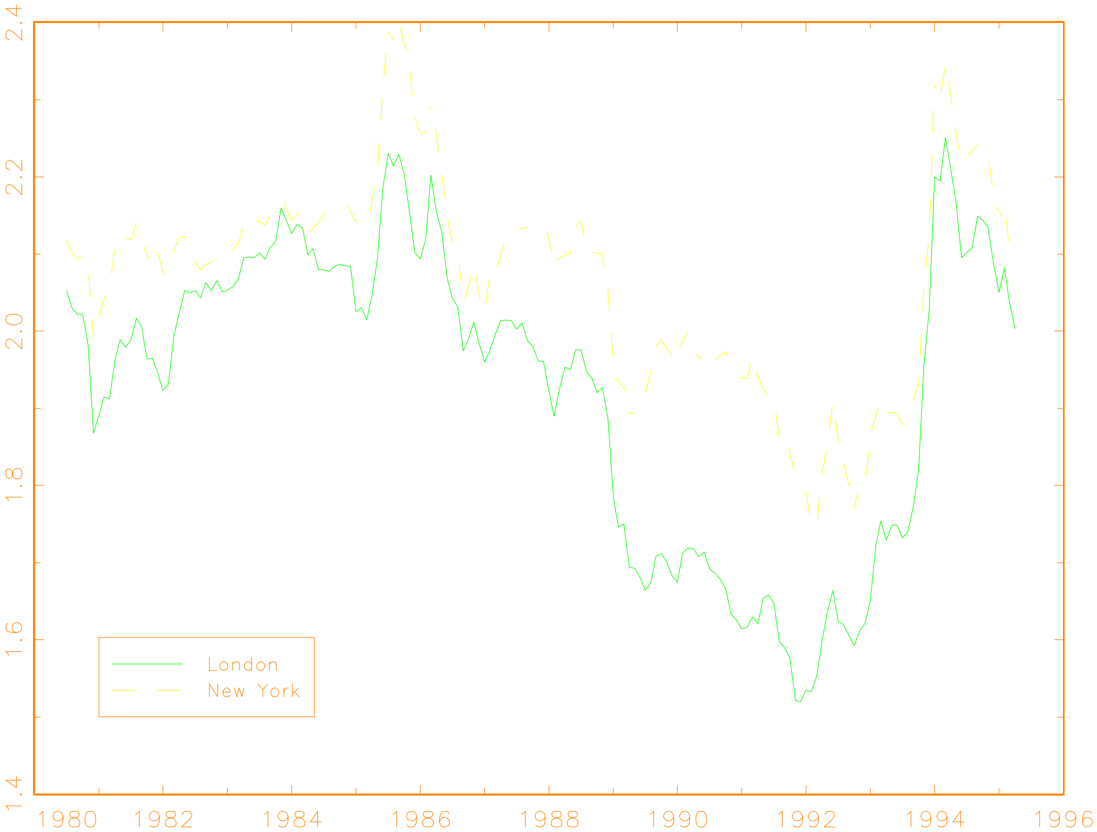

Figure 3: Logarithmic prices of coffee futures on the LIFFE and CSCE for the period 1981:1–1995:10.

Table 1: Univariate MA–ARCH models for the futures price series.

	Cocoa		Coffee	
parameter	London	New York	London	New York
μ	0.0007	0.0001	-0.0029	-.0019
	[0.29]	[0.04]	[-1.38]	[-0.83]
θ	0.403	0.27	0.152	0.052
	[9.32]	[3.90]	[2.76]	[0.59]
α_0	0.00073	0.00067	0.00056	0.00066
	[17.10]	[13.95]	[11.46]	[8.74]
α	0.00	0.100	0.667	0.558
	[0.01]	[1.31]	[4.88]	[3.75]

Note: Fitted models are of the form $x_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}$ with conditional variance equation $h_t = \alpha_0 + \alpha\varepsilon_{t-1}^2$. Figures in squared brackets are t–values.

4 Empirical results

4.1 Model estimation

As outlined in Section 3.1, the formal model with all its parameters is given as

$$\begin{aligned}
\mathbf{X}_t &= \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \boldsymbol{\varepsilon}_t + \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} \boldsymbol{\varepsilon}_{t-1} \quad , \\
\mathsf{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') &= \mathbf{H}_t \quad , \\
\mathbf{H}_t &= \begin{bmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ \rho & 1 \end{bmatrix} \\
& \quad \times \operatorname{diag}\left(\boldsymbol{\varepsilon}_{t-1}' \begin{bmatrix} a_{11} & a_{12} \\ a_{12} & a_{22} \end{bmatrix} \boldsymbol{\varepsilon}_{t-1}, \boldsymbol{\varepsilon}_{t-1}' \begin{bmatrix} b_{11} & b_{12} \\ b_{12} & b_{22} \end{bmatrix} \boldsymbol{\varepsilon}_{t-1}\right) \begin{bmatrix} 1 & \rho \\ 0 & 1 \end{bmatrix} \quad (4)
\end{aligned}$$

Note, however, that the matrices $\mathbf{C}$, $\mathbf{A}$, $\mathbf{B}$ are estimated in their Cholesky form in order to guarantee their positive definiteness. For example, $\mathbf{C}$ is formed as $\mathbf{C} = \mathbf{L}_c \operatorname{diag}(c_1^2, c_2^2)\mathbf{L}_c'$, where $\mathbf{L}_c$ is triangular with unit diagonal and thus depends on one parameter l_c only. The 'model parameters' c_{11}, c_{12}, c_{22} correspond to the 'technical parameters' c_1, c_2, l_c. Estimation is conducted by a quasi–ML algorithm that imposes normality on the errors $\boldsymbol{\varepsilon}_t$. Optimization of the likelihood function uses the BFGS algorithm of GAUSS that also calculates numerical standard errors and t–values. Due to near-singularities of some matrices, many of these standard errors appear fragile. Therefore, we will give the point estimates of all model parameters and t–values for all technical parameters, while we refrain from calculating t–values for the transformed model parameter estimates.

4.1.1 Cocoa futures: London and New York

The results of a bivariate MA–ARCH model for the two cocoa price variables p_{Lt}, p_{Nt} on the LIFFE and the CSCE, i.e., $\mathbf{X}_t = (\Delta \log p_{Lt}, \Delta \log p_{Nt})'$, are given in Table 2. The time-constant portion of the variance matrix $\mathbf{C}$ is small and the ARCH effects are quite important. Because the second diagonal entry is insignificant for both matrices $\mathbf{A}$ and $\mathbf{B}$, these are statistically singular and give much more weight to the London component. A non-trivial rotation parameter of 0.387 would indicate a time-changing conditional covariance but it remains insignificant. The first diagonal element in $\mathbf{C}$ is larger, by a magnitude, than the second one, hence time-changing volatility plays a larger role in New York than in London. In summary, it appears that volatility is mainly generated on the London futures market by unusual news, and this volatility then may also spread to the New York futures market. A likely explanation of this feature rests on the fact that the LIFFE is by far the larger market (see also Jumah *et al.*, 1999).

We note that the bivariate model apparently contradicts the univariate results (see Table 1), where no ARCH effects are found. This demonstrates the importance of multivariate modeling, as heteroskedasticity in covariance and other important cross-effects pass undetected in univariate analysis.

Table 2: Bivariate model for London and New York cocoa futures.

model	estimated parameter	technical	t–value
μ_1	-0.0004		-0.17
μ_2	-0.0006		-0.26
θ_{11}	0.546		7.05
θ_{12}	-0.150		-2.17
θ_{21}	0.046		0.53
θ_{22}	0.211		3.10
$10^2 c_{11}$	4.494	c_1	39.56
$10^2 c_{12}$	0.711	l_c	10.77
$10^2 c_{22}$	0.158	c_2	32.33
ρ	0.387		1.02
a_{11}	0.469	a_1	14.01
a_{12}	-0.212	l_a	-6.27
a_{22}	0.097	a_2	0.77
b_{11}	0.352	b_1	5.48
b_{12}	-0.139	l_b	-3.19
b_{22}	0.056	b_2	0.91

Note: The t–values in the last column correspond to the model parameters and their point estimates in the first and second column, except for those cases where a technical parameter was used in likelihood maximization and the model parameter was calculated indirectly. In those cases, the t–values correspond to the technical parameters as given in the third column.

4.1.2 Cocoa and exchange rates

The bivariate GARCH model for the London and New York cocoa futures gives a good impression of the way that the volatility evolves from one market to another. In order to investigate the importance of currency risk hedging in these effects, one may also investigate bivariate models, where one variable is a commodity price and the other is the exchange rate. We will proceed with logarithmic data series for all variables, as above.

A statistical analysis of the London cocoa futures yields the model given in Table 3. All risk in both series is simply explained by the volatility of the currency exchange rate. The second risk factor is small and insignificant. The first risk factor and the significant rotation parameter quantify the way that the exchange rate volatility spreads to cocoa prices, to the exchange rate itself, and to the covariance of the two variables. Again, the (2,1) entry in the MA matrix is small and exogeneity of the exchange rate is confirmed.

Table 3: Bivariate model for London cocoa futures and exchange rate.

model	estimated parameter	technical	t–value
μ_1	0.0004		0.02
μ_2	0.0005		0.03
θ_{11}	0.387		16.18
θ_{12}	0.305		12.73
θ_{21}	0.039		1.62
θ_{22}	0.413		17.22
$10^4 c_{11}$	6.888	c_1	6.66
$10^4 c_{12}$	0.603	l_c	0.10
$10^4 c_{22}$	1.010	c_2	4.12
ρ	0.754		31.54
a_{11}	0.0	a_1	0.00
a_{12}	-0.001	l_a	-23.74
a_{22}	0.104	a_2	0.83
$10^4 b_{11}$	0.002	b_1	1.09
$10^4 b_{12}$	-0.103	l_b	-0.43
$10^4 b_{22}$	6.707	b_2	1.01

Note: see Table 2.

For the New York cocoa futures (see Table 4), the second factor turned out to be insignificant altogether and was therefore omitted in order to overcome the ensuing convergence problems. The cocoa futures price series generates a small but statistically significant autonomous volatility that, by construction, influences both variables. However, this effect is comparatively small and should be interpreted with care. The general picture that is given by the London series is reproduced in this third experiment: the exchange rate is exogenous for means and variances, and the volatility in cocoa prices is mainly explained by the innovations of the exchange rate series.

Table 4: Bivariate model for New York cocoa futures and exchange rate.

model	estimated parameter	technical	t–value
μ_1	-0.0002		-0.11
μ_2	0.0005		0.53
θ_{11}	0.299		7.05
θ_{12}	0.226		6.41
θ_{21}	0.037		1.59
θ_{22}	0.454		11.05
$10^4 c_{11}$	7.387	c_1	44.12
$10^4 c_{12}$	-0.342	l_c	-1.77
$10^4 c_{22}$	1.021	c_2	32.17
ρ	2.176		63.31
$10^2 a_{11}$	0.002	a_1	0.34
$10^2 a_{12}$	-0.077	l_a	-3.46
$10^2 a_{22}$	3.673		

Note: See Table 2.

4.1.3 Coffee futures: London and New York

For the coffee futures prices we use the robusta quality in London and arabica quality in New York, as these qualities are the most representative for the two commodity exchanges. In the notation of (4), $\mathbf{X}_t = (\Delta \log p_{Lt}, \Delta \log p_{Nt})'$, hence the first variable is the (logarithmic growth rate of the) London price. For the statistical results, see Table 5. Again, the intercept vector is insignificant and this confirms the visual impression. At least two of the moving-average coefficients are significant and demonstrate the substantial short-run serial correlation in returns. Rank restrictions can be found, however, in the ARCH factors. The first factor matrix $\mathbf{A}$ appears to depend on $\varepsilon_{t-1,1}^2$ only, i.e., on the innovations of the London futures market. The second factor matrix $\mathbf{B}$ also has rank one and describes a second factor of the form $(b_1\varepsilon_{t-1,1} + b_2\varepsilon_{t-1,2})^2$ that depends on both innovations but again gives more weight to the London market. The large rotation parameter of 1.143 shows that the two ARCH factors influence the volatility in London as well as in New York and also cause non-trivial effects in the covariance between the markets.

4.1.4 Coffee and exchange rates

As in the case of the cocoa prices, we also estimated bivariate ARCH models for the coffee price series and the currency exchange rate series.

Estimation of fully parameterized structures yielded various parameter estimates with very low significance. After eliminating the insignificant parameters from the ARCH part of the model, we obtained a simplified model for the London futures series. This model is summarized in Table 6.

The first ARCH factor matrix $\mathbf{A}$ is singular and depends on a linear combination of currency exchange and commodity price shocks. The second ARCH factor is the exchange rate volatility. The rotation parameter was insignificant and was therefore omitted. Therefore, the first factor represents a 'joint' factor that determines the risk in the price series, whereas the second factor is a pure currency-risk factor that, independently, determines the volatility of the exchange rate. Note that the entries of the $\mathbf{C}$ matrix are of a much smaller scale than the ARCH factors, which gives a dominant role to time-changing risk.

A comparable experiment for the New York futures series gave qualitatively similar results, which are summarized in Table 7. Currency exchange

Table 5: Bivariate model for London and New York coffee futures.

model	estimated parameter	technical	t–value
μ_1	-0.0022		-1.02
μ_2	-0.0015		-0.71
θ_{11}	0.189		7.02
θ_{12}	-0.086		-3.20
θ_{21}	0.049		1.82
θ_{22}	0.035		1.23
$10^2 c_{11}$	2.403	c_1	27.81
$10^2 c_{12}$	0.041	l_c	8.51
$10^2 c_{22}$	1.273	c_2	27.40
ρ	1.143		39.11
a_{11}	0.819	a_1	30.77
a_{12}	-0.031	l_a	-1.31
a_{22}	0.002	a_2	0.69
b_{11}	0.300	b_1	18.43
b_{12}	-0.109	l_b	-12.24
b_{22}	0.040	b_2	-0.79

Note: See Table 2.

Table 6: Bivariate model for London coffee futures and exchange rate.

model	estimated parameter	technical	t–value
μ_1	-0.0029		-1.23
μ_2	-0.0001		0.08
θ_{11}	0.145		3.23
θ_{12}	-0.005		-0.18
θ_{21}	-0.014		-0.66
θ_{22}	0.430		10.40
$10^4 c_{11}$	5.338	c_1	25.84
$10^4 c_{12}$	0.462	l_c	1.92
$10^4 c_{22}$	1.153	c_2	32.17
a_{11}	0.695	a_1	24.03
a_{12}	0.269	l_a	11.27
a_{22}	0.104		
b_{11}	0.0		
b_{12}	0.0	l_b	-11.63
b_{22}	0.114		

Note: See Table 2.

rate and futures prices are even more detached than in the London model and generate their individual time-varying and mutually independent risk. The bottom line appears to be that hedging against currency fluctuations may play a much larger role on the London market than on the New York market.

Table 7: Bivariate model for New York coffee futures and exchange rate.

model	estimated parameter	technical	t–value
μ_1	-0.0020		-0.82
μ_2	-0.0001		0.12
θ_{11}	0.045		1.55
θ_{12}	0.136		4.76
θ_{21}	0.012		0.57
θ_{22}	0.419		14.34
$10^4 c_{11}$	6.440	c_1	27.91
$10^4 c_{12}$	0.228	l_c	0.94
$10^4 c_{22}$	1.121	c_2	32.99
a_{11}	0.599	a_1	30.73
a_{12}	0.0		
a_{22}	0.0		
b_{11}	0.0		
b_{12}	0.0	l_b	-13.14
b_{22}	0.142		

Note: See Table 2.

4.2 Forecasting

The models for the various commodity prices are compared according to prediction accuracy. A forecaster of agricultural commodity prices is assumed to target either predicting the future development of the price series in order to optimize the returns on her portfolio or to target risk prediction, maybe in order to sell commodities if an abnormally high volatility is indicated and thereby the probability of a large loss might increase. In the first case, the forecaster's target is well represented by an estimate of the conditional mean of the variable $\mathsf{E}(x_{t+1}|\mathcal{I}_t)$ and by the primary prediction error

$$e_{t+1|t} = \mathsf{E}(x_{t+1}|\mathcal{I}_t) - x_t \quad . \tag{5}$$

In the second case, the forecaster's target is better represented by the conditional variance of the variable $\mathsf{E}\{(x_{t+1} - \mathsf{E}x)^2|\mathcal{I}_t\}$. Because the true volatility at time $t+1$ remains unobserved, the second-order error

$$\varepsilon_{t+1|t} = \mathsf{E}\{(x_{t+1} - \mathsf{E}x)^2|\mathcal{I}_t\} - (x_{t+1} - \mathsf{E}x)^2 \tag{6}$$

may be a poor approximation to the forecaster's true loss. However, in the absence of such an observed volatility series, we will exclusively rely on functions of $\varepsilon_{t+1|t}$.

The traditional loss function in forecasting is the squared loss $l_2(x) = x^2$. Therefore, measures of prediction quality such as $l_2(e_{t+1|t})$ and $l_2(\varepsilon_{t+1|t})$ are commonly reported. This practice is open to criticism, however, as the forecaster's true loss function is not known and may even vary across persons in the profession. The possibility of asymmetric loss could also be taken into account. For simplicity, we focus on absolute loss $l_1(x) = |x|$ as a more robust alternative that gives less weight to occasional outliers. For a thorough discussion of prediction evaluation, see, e.g., Clements and Hendry (1998).

The first rows in the panels of Tables 8 and 9 report average squared and absolute prediction errors, both first-order and second-order, when the future price series are predicted over the last observed year, i.e., for the last 12 observations. Prediction is based on the bivariate ARCH models that include the commodity prices and an exchange rate as tabulated in the preceding section. The model specification is left constant over the interval but rolling predictions are calculated for every time point, hence all parameters are re-estimated for the relevant time periods. We note that some parameters become seemingly insignificant for such shortened intervals. Such effects may indicate seasonality in the commodity markets, as only a few observations seem to strongly alter the specification. We will consider the possible occurrence of seasonal effects at the end of this section.

We now turn to a comparison of the forecasting performance of these bivariate models that include the specific price and the dollar/sterling exchange rate with other specifications. Consider the London coffee futures price. Volatility in this series mainly depends on the London market and also on the exchange rate. We are therefore led to expect that the exchange

Table 8: Prediction errors for the coffee futures prices based on bivariate MA–ARCH models.

	$l_2(e)$	$l_1(e)$	$l_2(\varepsilon)$	$l_1(\varepsilon)$
London				
bivariate + exchange rate, restricted	16.10	3.153	2.795*	1.430
bivariate + New York	14.88*	3.061*	2.849	1.351
bivariate + New York, restricted	14.95	3.068	2.825	1.351*
univariate	16.02	3.147	2.866	1.425
New York				
bivariate + exchange rate	13.94	3.114	1.586	1.038
bivariate + London	16.05	3.359	3.068	1.368
univariate	13.84*	3.095*	1.549*	1.026*

Note: Columns were re-scaled by 10^5, 100, 10^6, 10^3 in this order. This scaling does not affect the comparison. The best prediction is marked with an asterisk.

Table 9: Prediction errors for the cocoa futures prices based on bivariate MA–ARCH models.

	$l_2(e)$	$l_1(e)$	$l_2(\varepsilon)$	$l_1(\varepsilon)$
London				
bivariate + exchange rate	3.287	1.427	0.251	0.451
bivariate (both futures)	2.939*	1.402*	0.209*	0.408*
univariate	3.341	1.431	0.262	0.464
New York				
bivariate + exchange rate	2.146*	1.072*	0.356*	0.556*
bivariate (both futures)	3.599	1.476	0.499	0.642
univariate	4.201	1.573	1.032	0.963

Note: See Table 8.

rate will show a relatively strong influence on prediction, while the New York futures price will not show any such influence. The results presented in Table 8 are, however, less clear. Accounting for the developments on the New York futures market apparently improves the mean prediction relative to univariate modeling or just accounting for the exchange rate. The squared-loss criterion suggests the use of exchange rate for loss prediction but the absolute criterion indicates that simple univariate ARCH modeling may be equivalent and utilizing the New York market may be slightly better. In summary, the differences across models for risk prediction are small and the ranking depends on the loss function. The differences between the restricted and the unrestricted models is small, hence we will analyze restricted models only for the remaining cases.

Now consider the New York coffee futures price. It was found that the causal direction from London to New York tends to dominate the reverse direction, and even more so with respect to explaining the volatility in the series. Therefore, we would expect that utilizing the London series might help to predict the New York volatility. We would also expect that utilizing the exchange rate might *not* help, as according to our bivariate model (7) the New York futures volatility does not depend on the currency exchange rate. Whereas the results that are shown in Table 8 support the latter hypothesis, the former one is not supported. The bivariate model for the London and New York coffee futures generates forecast failure on some occasions that transfers into an inferior average means forecast and further into a bad risk forecast. The univariate model dominates for all criteria.

We turn to the cocoa futures. From the estimation stage of the bivariate models we know that conditional volatility shows a causal direction from London to New York, hence we may expect an improvement in the risk forecast from utilizing bivariate models over univariate ones. We also found that the exchange rate risk is extremely important for both markets, hence we also are led to expect an improvement from utilizing bivariate models that include the currency exchange rate, as they were already used to generate Table 3. Table 9 shows that there are indeed noteworthy differences among the forecasting qualities of the three approaches but that these are mainly rooted in the means predictions. Models with bad means predictions then also cause inferior risk predictions. The univariate model does not predict well for New York. The innovations on the London market exert a substantial influence on the New York market with a lag of around one month, and ignoring this effect yields bad predictions. For the bivariate models, the ranking is different for the two markets. In London, a bivariate model with the two futures prices dominates the exchange rate model. The exchange rate model is only slightly better than the univariate forecast, which confirms the commonly observed fact that even very significant conditional heteroskedasticity is not always easy to exploit in forecasting. In New York, the exchange rate model is by far the best. We conclude that the reported spread of the volatility news from London to New York is really a spread of news concerning the exchange rate and that inclusion of the London price has no additional value for forecasting the New York price, although the situation is quite different for the London price itself.

Finally, we briefly address the issue of seasonal effects. Cocoa is harvested twice a year, with October to March representing the 'main crop' season and April to September representing the 'midcrop' season (see JUMAH, 1986). We found strong indication of corresponding seasonal effects in the cocoa series, where January, March, June, and August turned out to be the unusual months. In January and March, cocoa prices appear to show a downward tendency, everything else held constant, whereas in June and August the price appears to have a tendency to increase. The effect also appears to have some effect on forecasting. Note that intercept constants have otherwise been found to be insignificant. In the coffee series, however, we could not find such seasonal effects.

5 Summary and conclusion

Due to the existence of a strong association between exchange rate risk and relative price risk, foreign exchange investors increasingly shift from one currency into another, in order to exploit the expected difference in returns to holding assets across markets.

We analyze the extent to which volatility of inter-market spread for coffee and cocoa on the London LIFFE and the New York CSCE is influenced by the dollar/sterling exchange rate. The statistical evidence shows that exchange rate volatility affects cocoa futures prices on the LIFFE and CSCE. The same evidence was found for coffee on the London market but not on the New York market. We also find that the volatility in cocoa prices on the London market influences the price risk on the New York market. A similar mechanism appears to be at work across futures prices for coffee in London and New York.

In three out of the four cases — i.e., two commodities in two markets — that we investigated, the exchange rate posed as a main source of risk for the commodity futures price. It can be concluded that the significance and form of volatility spill-over effects of a bilateral exchange rate depend on the specific commodity and specific market.

Finally, we evaluate whether the detected volatility spill-over effects can be exploited for improving prediction accuracy. Unfortunately, we find that the possible gains in prediction may be small.

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Institut für Höhere Studien
Institute for Advanced Studies
Stumpergasse 56
A-1060 Vienna
Austria

Phone: +43-1-599 91-145
Fax: +43-1-599 91-163